VEHICLE ARCHITECTURE SELECTION FOR HIGH EFFICIENCY AND PERFORMANCE APPLICATIONS

Undergraduate Honors Thesis

Submitted to the Department of Mechanical Engineering

The Ohio State University

In Partial Fulfillment of the Requirements

For Graduation with Honors Research Distinction in Mechanical Engineering

Jacqueline Karl-DeFrain

May, 2019

ABSTRACT

The drastic spike in global fossil fuel consumption in the late 20th and early 21st century has quickly become cause for concern. Not only are fossil fuels a non-renewable resource, but the release of their combustion products into the atmosphere has a detrimental impact on the environment. With the world's energy consumption steadily trending upwards and the growth of the transportation industry in developing nations, the automotive industry is exploring alternative energy options. One area of research is electrified drivetrains, which include battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). Currently, the limited range and high cost of BEVs make them infeasible as a replacement for conventional vehicles. However, HEVs offer promise to maintain both high performance and efficiency without requiring significant infrastructure overhaul. General Motors, the US Department of Energy, and MathWorks sponsor the EcoCAR Mobility Challenge to adapt an existing market vehicle to a hybridized platform, improving overall efficiency and emissions while maintaining high performance to appeal to a broad customer market. The purpose of this research is to discuss Ohio State's architecture selection process for this student-driven competition. This design space exploration begins by broadly evaluating fuel consumption between conventional, HEVs and plug-in hybrid electric vehicles (PHEVs) for B20, E10, and E85 fuel types. Next, general electric motor configurations are evaluated for their impact on fuel economy. The design space exploration concludes with determining the optimal pairing of specific engine, transmission, energy storage system, electric motor, and transmission ratio options. Energy-based vehicle models are used to simulate realistic performance and fuel economy estimates. Additionally, dynamic programming evaluates each component configuration for optimized energy consumption. Completion of the architecture selection process yields an optimal architecture for meeting the Vehicle Technical Specifications (VTS) required by the EcoCAR Mobility Challenge.

ACKNOWLEDGEMENTS

I would firstly like to thank both Dr. Shawn Midlam-Mohler and Dr. Giorgio Rizzoni for their willingness to advise me during my BSMS career. In particular, Dr. Shawn has spent countless hours helping review and revise the architecture selection process. Without him, this project would not have achieved the same level of maturity. Dr. Rizzoni's passion for both student motorsports and the EcoCAR team have had a significant impact on my undergraduate career and continue to shape my current work.

I also would like to recognize the contributions made by other members of the Controls and Systems Modelling and Simulation team, Kristina Kuwabara and Mahaveer Satra. Their input and simulation work has helped shape the architecture selection process.

Finally, I would like to thank Stephen Squires III for his constant encouragement, support, and countless revisions. He has served as a major influence from the initial proposal of this project to final thesis and has kept me motivated throughout the length of my research.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

1.1 Background

The reliance of vehicles on fossil fuels has been an increasing area of concern in the 21st century. Although fossil fuels are used in all energy applications, the transportation industry is the largest energy consumer and relies almost entirely on petroleum, with some small contributions from biomass, natural gas, and electricity [1].

The use of petroleum is complicated by both environmental and economic concerns. The burning of petroleum releases carbon dioxide, a greenhouse gas linked to global warming. In addition, it is widely known that fossil fuels are a nonrenewable resource. As easily accessible reserves are used up, more time and money must be spent to develop new drilling techniques to extract oil from more difficult to reach places [2]. Figure 1 shows the increasing consumption of fossil fuels from a global perspective [3]. In modern years, this has increased exponentially, largely due to growth in the transportation sector. This increase in consumption, combined with finite availability, supports a need to develop alternative solutions.

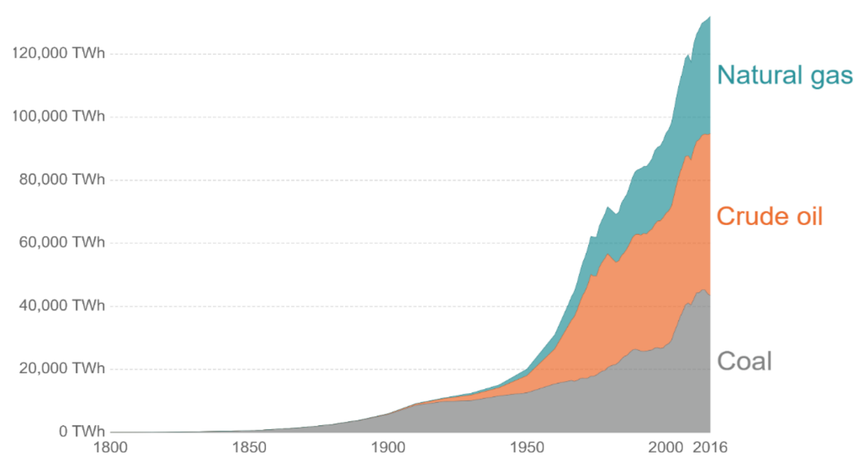


Figure 1: Global Primary Fossil Fuel Consumption, in Terawatt-Hours [3]

In the effort to reduce the use of fossil fuels, alternative energy solutions have been a growing area of research. Some of the most popular include higher efficiency applications of natural gas, liquefied petroleum gas, and blended fuel, as well as alternative energy sources such as methanol, ethanol, hydrogen, and electricity [4]. However, many of these fuels face major challenges to widespread implementation. Natural gas and hybrid require storage at cryogenic temperatures, which is both expensive and difficult to build and maintain [4]. Additionally, the infrastructure for other fuels, such as liquified petroleum gas, does not currently exist. Finally, natural gas, liquefied petroleum, and alcohols all still contribute to emissions. Electric vehicles produce zero emissions pump-to-wheel, meaning from the vehicle itself, but electricity may still be generated using natural gas, coal, and petroleum. Although electricity generation often requires fossil fuels, it also takes advantage of renewable resources, such as solar, nuclear, hydro, wind, and geothermal power [1]. Thus, electricity is the most viable alternative clean energy solution.

Electricity can be utilized in a variety of ways to power a vehicle. Fully electric vehicles, or Battery Electric Vehicles (BEVs), feature a battery pack as the primary power source. Although this vehicle configuration does not have any of the drawbacks of charging or refueling, batteries of this type are expensive to produce and difficult to dispose of properly [4]. Plug-in Hybrid Electric Vehicles (PHEVs) utilize the grid to charge a battery pack that stores and distributes power to the car. Typically, the electric range is limited on these vehicles and they come with a backup traditional power source, such as an engine [5]. Finally, Hybrid Electric Vehicles (HEVs) utilize a battery to store charge and electric motors to generate and distribute electrical energy. These come in series and parallel configurations [5].

1.2 EcoCAR Mobility Challenge

Between the feasibility of implementation and their benefits to reducing emissions and fuel consumption, hybrids have garnered a lot of interest in this research area. The Advanced

Vehicles Technology Competition (AVTC) explores this through the EcoCAR Mobility Challenge (EMC).

This four-year competition is focused on the implementation of hybridized powertrains while maintaining performance characteristics of a 2019 production General Motors (GM) Blazer. Sponsored by GM, Argonne National Labs, and the Department of Energy, the competition aims to introduce students to this growing research field. Selected university teams will explore innovative Connected and Automated Vehicle (CAV) technologies and implement advanced propulsion systems to maximize vehicle efficiency while preserving performance. Year 1 of the competition will focus on the design of the vehicle architecture to meet specific VTS, outlined in Table 1 [6].

Table 1: Competition Vehicle Technical Specifications

Specification	**Competition Target**	**Minimum Requirement**
Acceleration, IVM-60 mph [s]	6.0	9.0
Acceleration, 50-70 mph (Passing) [s]	6.5	TBD
Fuel Economy [mpg]	33.5	Stock
Emissions	Stock	Stock
Gradeability [% grade @ 60 mph for 20 minutes]	N/A	3.5
Vehicle Top Speed [mph]	80.23	80.23

Later years of the competition involve mechanical fabrication and integration, controller development, as well as implementation of CAV technologies, following the timeline provided in Figure 19 in the Appendix [6]. In particular, implementation of the CAV system and use of sensor data is expected to play an integral role in Years 3 and 4. Although competition has yet to finalize specific targets, teams are expected to be able to execute SAE Level 1 and 2 autonomous capabilities such as Automated Lane Changes, Lane Keep Assist, Adaptive Cruise Control, and

Vehicle to X (V2X) communication [7]. Initial decisions made in Year 1 should take CAV integration into account to ensure the ability to meet targets in later competition years.

1.3 Overview of Thesis

Vehicle architecture is the focus of Year 1 and involves the selection and integration of an engine, transmission, electric machines, and a battery. This study aims to determine the optimal powerflow and specific components for the OSU EcoCAR Team that minimize fuel consumption and emissions while meeting performance targets.

This purpose will be achieved through meeting the following objectives:

- Benchmarking the previous competition's vehicle architectures and analysis methods
- Performing initial energy comparisons for a wide range of hybrid vehicle configurations
- Building higher fidelity vehicle models to simulate the fuel economy and performance of specific component configurations
- Reporting the selection process and final optimal architecture in the Architecture Selection Report

Chapter 2 focuses on relevant research to define key terms and components related to vehicle architecture and powerflow configurations. The selection process and vehicle performance of the previous EcoCAR competition will also be studied in depth. The finalized methodology, simulation tools, and initial design space limitations are presented in Chapter 3. Chapter 4 contains results and the final optimal architecture. Future work and applications beyond EMC Year 1 are summarized in Chapter 5.

CHAPTER 2: LITERATURE REVIEW

This chapter compiles background research conducted on design space exploration and hybrid propulsion architectures as well as exploring similar work performed in this field. The first section is a review of academic resources on both design filtering techniques and different hybrid propulsion systems to yield a thorough understanding of the design space created by powerflow and electric motor options. The second section is a reflection on the architecture selection process of the previous AVTC, EcoCAR 3.

2.1 Literature Review

In order to arrive at an ideal hybrid architecture for meeting team VTS, a large design space must be explored created primarily by the combination of various components. A filtering technique can be applied to incrementally reduce large design spaces from millions of configurations to a few remaining options. This can be done based on both dominance criteria and Pareto analysis.

Dominance filtering uses specific criteria to evaluate candidates; if Candidate "A is superior or equal to B with respect to every criterion of evaluation and distinctly superior with respect to at least one criterion" [8], it can be considered to dominate Candidate B. Dominated designs are filtered out, reducing the design space. Retained candidates can be used to compare against any new options as they emerge. Evaluation criteria do not need to be independent for this analysis technique; when interdependent criteria are used to investigate performance tradeoffs, the remaining design space will be bigger than if independent criteria are used [8].

After dominance filtering has been applied, the surviving set can be further reduced through a Pareto analysis, where improvement on any one criterion will reduce its performance for another criteria [9]. This is visualized in a tradeoff diagram, which is a two dimensional scatter plot where the axes are a pair of design criteria [8]. These diagrams allow the designer to identify candidates that have interesting properties and consider those options across different measures. The initial dominance filtering helps reduce the design space to a manageable amount that can be observed and evaluated by the designer directly. The result of this exploration process arrives at one or a few optimal candidates. This design space exploration technique can be applied to the selection of an ideal hybrid architecture for the EMC. In order to understand the different component combinations that comprise this space, a literature review of hybrid-specific configurations and components has been conducted.

Hybrid Electric Vehicles (HEVs) utilize an internal combustion engine (ICE), a battery, and electric motors to generate, store, and distribute electrical energy. The main distinction in hybrid vehicles is powerflow through the drivetrain, operating in either series and parallel modes. The series HEV couples the engine to a generator, which is used to charge the battery pack. The pack connects to an electric machine, which drives the wheels [5]. Series hybrids are considered electric intensive since they can operate in electric vehicle (EV) only mode, turning the ICE on only when the battery state of charge (SOC) falls below a certain threshold [10]. The mechanical disconnect between the ICE and wheels allows the engine to run at its optimal operating point, resulting in low fuel consumption. On the other hand, parallel HEVs are considered engine intensive, having both a downsized engine and electric machine connected directly to the wheels in parallel [10]. This allows the vehicle to blend torque from each source to meet performance targets. Typically, the electric motor is used alone at low speeds while the ICE operates alone at high speeds [10]. In engine-only operation, the electric motor may serve as a generator to charge the battery.

In addition to the powerflow of a hybrid architecture, the electric motor placement is an important characteristic that impacts the integration cost, fuel efficiency, and performance of the vehicle. Electric motors can be positioned in the locations called out in Figure 2 [11].

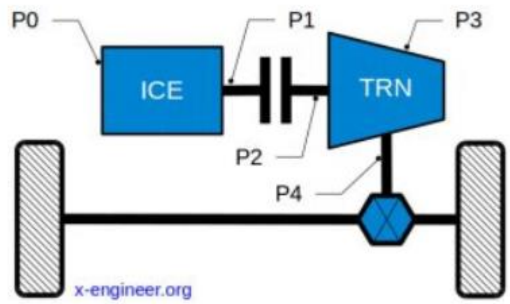


Figure 2: Electric Motor Placement Options [11]

P0 motors are directly connected to the ICE through a belt on the front end accessory drive. They are typically easy to integrate by simply replacing the conventional 12V alternator with a 48V electric machine [11]. The primary advantages of P0 motors are ability to implement start/stop functionality, regenerative braking, and additional propulsion torque. However, their mechanical connection to the ICE is a disadvantage, as the engine friction torque is a parasitic loss. In addition, mechanical restrictions of a belt limit their torque capabilities [11].

A secondary pre-transmission electric motor is a P1, which connects directly to the engine crankshaft. Similar to the P0, this electric motor's functions include start/stop, engine load shift, torque assist, torque boost, sailing/coasting, energy recovery, and brake regeneration [11]. P1 motors can provide higher torque than P0s but, because of the direct connection between the P1 and crankshaft, the torque requirements can be high. Overall torque output is limited based on the electric motor size, and energy recovery is affected by engine friction losses [11]. In addition, P1s have a high impact on pre-existing architectures, making integration challenging and costly.

Pre-transmission motors are connected directly to the engine and thus do not allow energy recovery with the engine off. P2, P3, and P4 motor configurations are decoupled from the engine and feature more efficient powerflow. However, post-transmission motors cannot take advantage of start/stop functionality by themselves.

P2 motors can either be side-attached, using a belt, or integrated between the ICE and transmission [11]. These motors have increased energy recover potential due to the removal of engine friction losses and can also provide electric creep and recover energy during vehicle coasting [11].

P3 and P4 motor configurations offer the highest energy recovery potential because they can generate energy without being impacted by engine or transmission losses. They are typically used for EV operation, provided the electric machine is capable of producing high torque [11]. P3 motors are connected to the transmission while P4 motors are connected to the rear axle, both through a gear mesh [11]. Because the front axle is powered by the ICE and the rear axle by an electric motor, P4 configurations allow four-wheel drive capabilities.

In summary, the literature review differentiates between types of hybrid electric powertrains, HEV and PHEVs, as well as the basic operating modes. With a hybrid electric vehicle, the electric motors can be integrated in a variety of ways. The different motor configurations impact the function, efficiency, and integration risk.

2.2 EcoCAR 3 Benchmarking Study

Although the previous AVTC, EcoCAR 3, differs from the Mobility Challenge in terms of scope of autonomous technologies and specific VTS goals, the design process for selecting a vehicle architecture is similar. EcoCAR 3 focused on the hybridization of a GM Camaro over a four-year period. The 16 competing teams were broken up into quartiles based on their performance in Year 4 of EcoCAR 3. One team from each quartile was chosen in order to examine their selection process, execution of design, and vehicle performance.

Quartile 1: The Ohio State University (OSU)

The Ohio State team placed first overall in the previous competition cycle, using the P0-P3, parallel-series PHEV shown in Figure 3 [12]. Table 1 shows the primary components of the architecture along with the sizing strategy used.

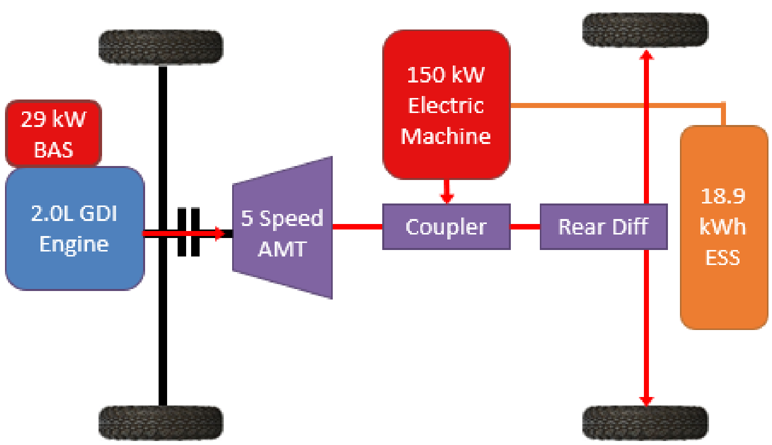


Figure 3: OSU Vehicle Architecture [13]

"OSU designed their vehicle around the emissions and energy consumption event (E&EC), which required a tradeoff in performance and drive quality" [13]. The prioritization of emissions and fuel economy was determined based on a cost function analysis of the competition points.

Table 2: OSU Component Breakdown and Sizing [13]

Component	Function	Sizing Approach
2.0 L E85 Naturally Aspirated (NA) Engine	Traction Torque	**Fuel:** Monte Carlo Analysis **Size:** Autonomie for Acceleration VTS
32 kW Denso Belted Alternator Starter	Assist with Engine Start Stop	**Size:** Autonomie for Fuel Economy VTS
112 kW Parker Hannifin Electric Machine	Traction Torque and Regenerative Braking	**Size:** Autonomie for Fuel Economy VTS **Ratio:** Max Ratio for Acceleration
18.9 kW-hr A123 Battery Pack	40 mi of EV Range and Energy Storage System (ESS)	**Size:** Monte Carlo Analysis
5-Speed Tremec Automated Manual Transmission	Torque Multiplication	**Ratio:** Only Available Ratios

The major advantages of this architecture were the high fuel economy, successfully implemented design, and avoidance of design penalties. Fuel economy was more heavily weighted than performance, which allowed the team to place first in two of the highest scoring point events. In addition, risk analysis was incorporated into the selection process. This resulted in choosing an architecture that could be implemented within the four-year timeline and with available resources. Finally, the team chose to avoid design penalties. Although this resulted in more design work early in the competition cycle, no penalties were accrued for cargo capacity, seating capacity, or vehicle range requirements.

Despite the necessary tradeoff between efficiency and performance, the 2.0L NA engine was a shortcoming of this architecture as it resulted in slower vehicle acceleration. This hurt the team in the acceleration and autocross events. Another downside was the incurrence of a cost penalty, due in part to having the largest battery pack, as well as generally more expensive components.

Quartile 2: University of Tennessee (UT)

The University of Tennessee team placed sixth overall in the EcoCAR 3 competition [12]. They chose an E10 P3 HEV, shown in Figure 4.

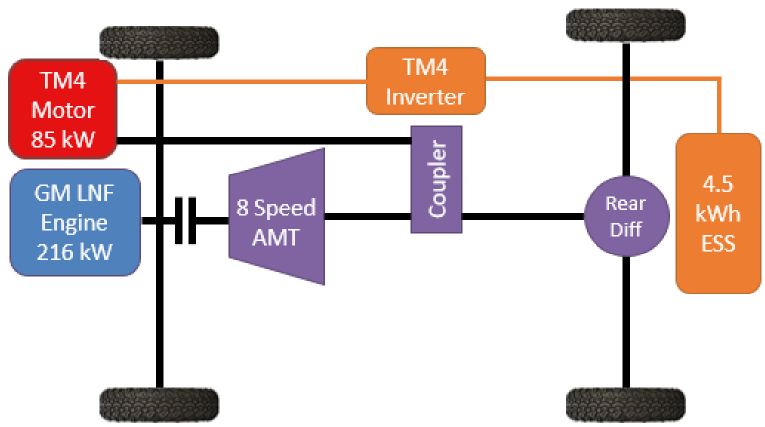


Figure 4: University of Tennessee Architecture [13]

The team focused on maximizing performance while not exceeding their ability to execute the chosen design. Rather than evaluating the point distribution, the team defined a target market based on sports car customers. This drove the team's primary focus towards performance and handling. The chosen components for this architecture are listed in Table 3. In contrast to Ohio State, the UT team chose components in part based on familiarity rather than simulation results.

Table 3: UT Component Breakdown and Sizing [13]

Component	Function	Sizing Approach
Turbocharged E10 I4 GM LNF	Traction Torque	**Size:** Availability and Familiarity
TM4 85 kW	Traction Torque and Regenerative Braking	**Size:** Peak Power Requirement
4.5 kW-hr A123 Battery Pack	Tractive Power and ESS for Regenerative Braking	**Size:** Single Module ESS for Simple Integration
GM 8L45 Transmission	Torque Multiplication	**Ratio:** No Justification Provided

The major advantage of choosing a P3 HEV was UT's final results in performance related events. They placed 1st in the 50-70 acceleration event and 2nd in the 0-60 event [12]. While Tennessee met their focus on performance, the vehicle architecture had poorer emissions performance, propulsion systems efficiency, and ESS packaging. In addition, they chose to design their transfer case in-house, which resulted in major backlash issues later in the competition. The backlash was partially resolved with their control strategy, but this component reflected the risk associated with custom machined gears.

The team's prioritization of performance reflected itself in the acceleration events. However, the major disadvantages of this architecture were the acceptance of the cargo penalty and poor fuel economy. Without considering the competition breakdown, the team lost points in these critical areas, resulting in a sixth place finish.

Quartile 3: University of Washington (UW)

The University of Washington team fell into the third quartile of competition, placing 11th overall [12]. They designed a series hybrid vehicle with independently-driven wheels to enable torque vectoring, shown in Figure 5.

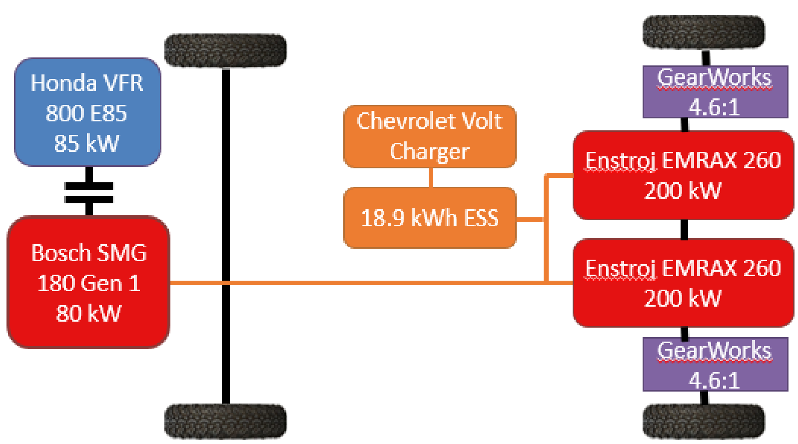


Figure 5: University of Washington Architecture [13]

UW's focus was primarily on improving the Camaro's longitudinal and lateral performance characteristics. However, in their architecture selection process, they did not report utilizing any type of optimization method for component sizing. They instead first selected components and then used Autonomie to verify choices met their VTS targets. Their component choices are shown in Table 4.

Table 4: UW Component Breakdown and Sizing [13]

Component	Function	Sizing Approach
85 kW 800c E85 NA Engine	Generator Torque Source	**Size**: No Justification Provided
Two 200 kW Emrax 268	Traction Torque	**Size**: Autonomie or Acceleration VTS
80 kW Bosch SMG 180	50 Miles of EV Range and ESS	**Capacity**: Autonomie for 50-mile CD Range
Two Custom Planetary Gearbox	Torque Multiplication	**Ratio**: Parametric Study to Maximize Use of Tire Traction

The University of Washington vehicle did not run as intended in competition due to major integration issues as well as drivetrain design flaws. Additionally, the team's custom transmission was not able to achieve high efficiency, limiting motor torque during competition. Overall, the team did not meet any of their VTS except for braking distance.

Quartile 4: Mississippi State University (MSU)

Mississippi State finished thirteenth overall with a series-parallel PHEV, shown in Figure 6. This architecture was chosen based on team calculations that showed a fuel economy of 99.7 mpgge and an improved initial vehicle movement (IVM)-60 mph and 50-70 mph time over the stock vehicle.

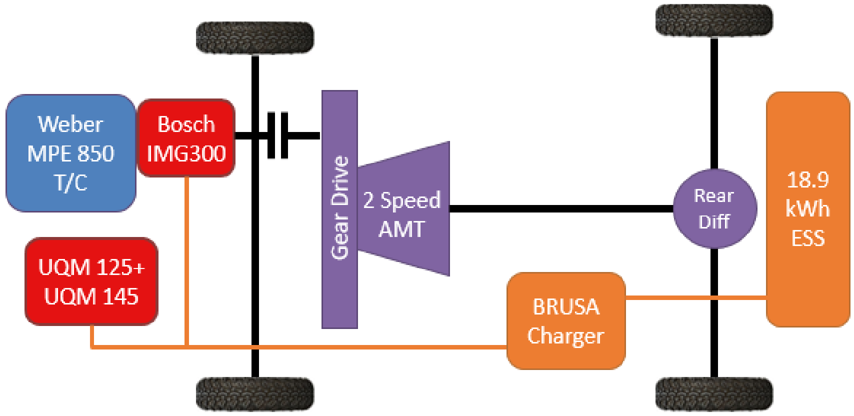


Figure 6: Mississippi State Architecture [13]

MSU did not report a clear design target such as drive quality, fuel economy, or performance. From their calculation justification, they attempted to make significant improvements to both fuel economy and performance. They utilized Autonomie to size components and simulate performance test results, as shown in Table 5.

Table 5: MSU Component Breakdown and Sizing [13]

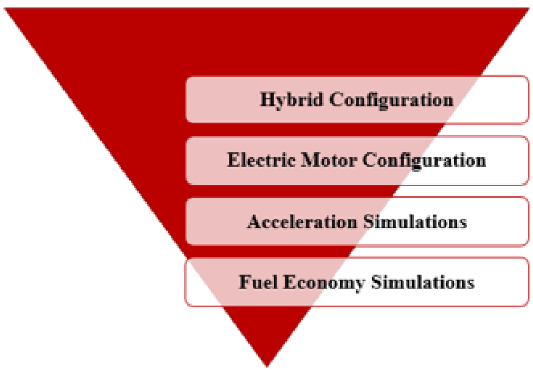
Component	Function	Sizing Approach
Weber 850 cc E85 T/C Engine	Traction Torque	**Size**: Autonomie for Fuel Economy Validation
Bosch IMG300	Assist with Engine Start Stop and Generator	**Size**: No Justification Provided
UQM 125 kW motor	Traction Torque and Regenerative Braking	**Size**: Autonomie for Acceleration Validation **Availability**: EcoCAR 1 Component
UQM 145 kW motor	Traction Torque and Regenerative Braking	**Size**: Autonomie for Acceleration Validation **Availability**: EcoCAR 1 Component
18.9 kW-hr A123 Battery Pack	27 mi of EV Range and ESS	**Size**: Space Claim and Autonomie for Gradeability VTS
Gear Vendors 2-Speed Overdrive Transmission	Torque Multiplication	**Ratio**: Only Available Ratio

This architecture offered high longitudinal performance potential with 125 kW and 145 kW traction motors. However, dynamic events were not run as intended due to the use of a normally-closed clutch as an open clutch, which resulted in a major clutch failure. Overall, the use of multiple high-risk components caused integration issues that prevented the team from completing all the events in Year 4. The team also chose an engine that did not meet US emissions regulations, which prevented them from participating in the E&EC event.

From the benchmarking study, it can be concluded that a cost function analysis of the competition point breakdown is imperative. In a real-world application, this would be akin to having an accurate customer market analysis. In addition, the use of simulation results to guide the decision-making process proved more beneficial than justifying previously selected choices. Finally, the complexity of the architecture had a significant effect on a team's ability to run as intended in the final years of the competition. Custom-designed components often resulted in lower efficiency and reliability due to team's lack of experience and professional equipment. The team will build off this process for the Mobility Challenge to design an architecture that is both high performing and achievable.

CHAPTER 3: TOOLS AND METHODS

The general process for the architecture selection is shown in Figure 7. The initial steps limit the design space by factoring in competition constraints as well as generic simulation results, limiting potential powerflow options, fuel sources, and electric motor configurations. From the remaining architectures, higher fidelity models are used to eliminate component configurations that do not meet baseline fuel economy and performance requirements. The last stage considers ideal fuel economy and available optimization space to determine a final architecture.



Stage	Simulation	Purpose	Component Configurations
1	GREET	Determine Hybrid Type	12,096
2	Autonomie Monte Carlo	Electric Motor Configuration Statistical Analysis	3,456
3	Autonomie	Acceleration Simulations	288
4	Autonomie	Initial Energy Consumption Simulations	79
	Dynamic Programming	Optimal Energy Consumption Simulations	

Figure 7: Vehicle Architecture Selection Process

Figure 7 highlights what simulation or analysis tools will be used in which stage of development. The first two stages are used at a high level to eliminate different hybrid architectures. Stages 3 and 4 focus on elimination of specific component configurations.

3.1 Competition Considerations

One major benefit seen from the EcoCAR 3 benchmarking study was the point breakdown analysis to determine OSU specific VTS. The point breakdown of each year was analyzed and divided in terms of acceleration, propulsion, performance, cost, efficiency, emissions, and CAV contribution, shown in Table 6. Comparing the percent of points associated with each of these categories allowed the team to identify which characteristics are most strongly weighted. Based on the major impact of drive quality, integration risk should be minimized. For the architecture selection process, acceleration performance and efficiency are the two major simulation considerations. Efficiency is weighted more heavily than performance and is reflected in the selection process through two iterations of energy consumption simulations.

Table 6: Competition Event Point Breakdown

Year	CAV	Drive Quality	Performance	Efficiency	Emissions	Total
1	0	0	0	0	0	0
2	50	112.5	72.5	50	0	285
3	167	141	67	102.5	22.5	500
4	235	165	62.5	115	22.5	600
Total	452	418.5	202	267.5	45	1385
Percentage	**33%**	**30%**	**15%**	**19%**	**3%**	**100%**

In addition to outlining the point breakdown of EMC, competition offers a variety of sponsored components and support to aid students in the process of designing and building a functional hybrid vehicle. A stock 2019 GM Blazer is donated to all teams as the base vehicle to be hybridized. In addition, GM engine and transmission pairs, referred to as powercubes, and Energy Storage System (ESS) options are offered as well.

Based on the introduction of CAV technology, competition aims to reduce the scope of the propulsion system design and integration. This will streamline the mechanical aspects of the vehicle to allow teams to focus more heavily on implementing SAE Level 1 and 2 autonomous capabilities such as Automated Lane Changes, Lane Keep Assist, Adaptive Cruise Control, and Vehicle to X communication. As a result, GM is offering five powercube options that feature calibrated engine/transmission pairs that are currently used in market vehicles. These options are detailed in Table 7. They can be split up for integration of a P1, P2 motor, or used in conjunction with a non-sponsored engine or transmission.

Table 7: Sponsored Powercube Options [7]

Powercube Option	Engine			Transmission			
	RPO Code	Displacement	Intake System	RPO Code	Number of Gears	Accumulator	ETRS
1	LYX	1.5L	Turbocharged	M3U	9	Y	Y
2	LTG	2.0L	Turbocharged	M3D	9	Y	N
3	LTG	2.0L	Turbocharged	M3E	9	Y	N
4	LTG	2.0L	Turbocharged	M3H	9	Y	Y
5	LCV	2.5L	Naturally Aspirated	M3D	9	Y	N

While other engine and transmission options may be considered for better fuel economy and performance characteristics, any additional component pairs must match or surpass GM powercube options in terms of integration. Given that OSU experienced major issues associated with drive quality in EcoCAR 3, choosing to integrate a non-sponsored engine and transmission is expected to take a significant amount of resources to achieve at any level of competitiveness.

The Department of Energy is sponsoring black box ESS for all teams. A student-built ESS is strictly prohibited. The additional control and benefit that a custom-built pack might offer is paired with higher complexity, integration risk, and major safety concerns. The available ESS options include a GM Chevrolet Malibu pack and a HDS pack, shown in Table 8, as well as a stipend to acquire a comparable black box ESS. The HDS option entered the architecture selection late, and was not evaluated until Stage 4. It was assumed that a larger battery pack would not significantly reduce the performance numbers evaluated in Stage 3. The HDS battery pack was not finalized at the time of this selection process; Table 8 reflects the most recent information released by competition.

Table 8: Sponsored ESS Comparison [7]

ESS Specifications	GM Malibu ESS	HDS Design Parameters
Discharge Power	52 kW	90 kW
Usable Energy	450 Wh	1500-2000 Wh
Total Energy	1.5 kWh	5500 Wh
Nominal Voltage	300 V	346 V
Mass	43 kg	35 kg
Volume	0.034875 m^3	0.104625 m^3 (estimate)

3.2 Stage 1: Hybrid Configuration Determination

The initial design pool contained 12,096 possible component configurations for a variety of different hybrid architectures. Argonne National Laboratory's GREET software was utilized to determine optimal fuel type and hybrid vehicle architecture for a midsize SUV [14]. The Mobility Challenge limits the competition to E10, E85, and B20 fuel sources [6]. E85 was eliminated as an option prior to GREET simulations due to unsupported calibrations for the GM powercube options. Conventional, HEV, and PHEV architectures were simulated with E10 and B20 to compare fuel economy and energy consumption.

3.3 Stage 2: Electric Motor Configuration

For Stage 2, more combinations were eliminated through low fidelity, rapid prototyping of different electric motor configurations in Autonomie. This is another Argonne National Laboratory software that provides fully customizable, energy-based vehicle models. It was developed to assess the impact of component sizing and technologies, powertrain configurations, and vehicle controls on energy consumption and vehicle performance [15]. Preexisting vehicle architectures and component data are housed in its database. P0, P1, P2, P3, P4, and P0-P4 stock Autonomie vehicle models were utilized. The engine peak power, total electric peak power, ESS, front drive ratios, and final drive ratios were set the same across all hybrid architectures to serve as control variables. The competition specific EMC city and highway cycles were uploaded and an allowable trace miss of $\pm$1% specified. The fuel economy results of each drive trace were used in the competition-provided Equation 1 to yield a combined EMC fuel economy estimate.

$$FE_{EMC,\,Combined} = \frac{1}{\frac{0.55}{FE_{EMC,\,City}} + \frac{0.45}{FE_{EMC,Highway}}} \qquad [1]$$

Due to the emphasis on drive quality in the competition point breakdown, integration risk was factored in at this phase. Fuel economy was weighed against risk for each motor configuration. A performance versus risk analysis was generated based on EcoCAR 3 architectures and their resulting final scores. In addition, literature was used to evaluate integration challenges associated with each motor option.

After selecting the electric motor placement, a Monte Carlo simulation was then used to consider the benefits of a 48V system variant over a high voltage option. Monte Carlo simulations are a statistical analysis method used to assess the uncertainty associated with a particular occurrence. This method is useful when the metric of interest, i.e. winning the competition or winning a specific event, depends on multiple, complicated probability distributions [16]. The point distribution of the Emissions and Energy Consumption (E&EC) event was used to generate the fuel economy cost function while the acceleration characteristics were captured by the relatively scored acceleration test. These were combined with the cost of ownership points to generate the metric of interest for the Monte Carlo simulation, shown in Equation 2.

$$total\ points = efficiency\ points + cost\ points + performance\ points \qquad [2]$$

The efficiency, cost, and performance points are all dependent on individual vehicle configurations as well as the number of points earned by other vehicles. An overview of the relevant competition-dictated equations is provided below, with the corresponding MATLAB script in the Appendix [7].

The cost points normalize each individual vehicle's cost of ownership over the total ownership cost of all competing vehicles and multiplies that by the maximum number of cost points available. The cost of ownership is determined in Equation 3.

$$total\ ownership\ cost = (purchase\ price) + (total\ fuel\ cost) - (resale\ price) \qquad [3]$$

where

$$purchase\ price = (motor\ cost + battery\ cost + engine\ cost) - stock\ propulsion\ system\ cost$$

$$purchase\ price = \left(\frac{\$6}{kW} motor\ size + \frac{\$20}{kW} battery\ size + engine\ cost\right) - \$3174.10$$

Engine cost is dependent on peak power, number of cylinders, presence of a boost system such as a turbocharger or supercharger, and presence of direct injection. Spark ignition engine cost is calculated according to Equation 4 and compression ignition engine cost according to Equation 5. Fuel cost is determined according to Equation 6.

$$EngCost_{SI} = [827 + 109 \times NoCyl + 6.2 \times EngPwr + 283 \times DI + 1730 \times Boost] \qquad [4]$$

$$EngCost_{CI} = 1294 + (518 \times NoCyl) + (8.05 \times EngPwr) \qquad [5]$$

$$total\ fuel\ cost = \left(\frac{fuel\ price\ \left[\frac{\$}{gal}\right] \times 30000\ [mi]}{fuel\ economy\ [mpg]}\right) \qquad [6]$$

Fuel price is based on the US Energy Information Administration 2022-2024 projections, given in Table 9 [7]. Fuel economy was assumed as 33.5 mpg, which is the competition VTS of a 15% improvement over the stock Blazer.

Table 9: Projected Fuel Price [7]

Fuel	Price
Diesel	\$3.43/gal
E10	\$3.19/gal
E85	\$2.83/gal
Premium	\$3.74/gal

$$resale\ price = purchase\ price\ \times (100\% - 25\%)$$

Assuming the vehicle depreciates 25% over 18 months and 30,000 miles.

The Monte Carlo simulation defined an event to reflect the competition, with twelve vehicles competing against each other. Randomly generated numbers of 48V P0-P4 and HV P0-P4 configurations were selected for each event, with all architectures running with the same engine option. The 2.0L turbocharged engine was chosen to do a baseline comparison. The probability of each architecture winning was calculated, depending on the total points function and associated probability distributions. This event was iterated 50,000 times to generate the overall probability of each architecture option winning the competition.

When randomizing fuel economy and acceleration results for the different architectures, the baseline numbers shown in Table 10 were assumed based on stock Autonomie data. Analysis of market vehicles shows 48V systems offer a fuel economy savings of 7-10% with a 6-20kW battery, while a HEV could improve 20-30% with a 20-40kW battery [17].

Table 10: Monte Carlo Performance Assumptions

Vehicle Configuration	Acceleration	Fuel Economy
P0-P4 48V	7.5	15% Improvement
P0-P4 HV	7.0	25% Improvement

The conclusion of Stage 2 finalized the hybrid architecture. Stages 3 and 4 then focus on optimizing specific component configurations within this design space.

3.4 Stage 3: Acceleration Simulations

Stage 3 evaluated the performance of 144 component combinations, shown in Table 11.

Table 11: Stage 3 Considered Components

Engine
Non-GM 1.6L Diesel
GM 1.5L Turbo
GM 2.0L Turbo with 2.89 front drive ratio
GM 2.0L Turbo with 3.17 front drive ratio
GM 2.0L Turbo with 3.8 front drive ratio
GM 2.5L NA

Final Drive Ratio
6.54
7.17
8.0
8.28
8.76
9.06

Electric Motor Size [kW]
30
55
80
117

The third phase of the architecture selection focused on performance simulations, particularly IVM-60 mph time. While both IVM-60 mph and 50-70 mph times are necessary VTS, the IVM-60 mph time is a more aggressive metric. The ability of the final architectures to meet 50-70 mph time will be validated for the final proposed architecture. The acceleration simulations used the stock Autonomie architecture model for the optimal motor placement. Vehicle models were created to reflect specific combinations of components listed in Table 11 by scaling the engine and electric motor peak power as well as implementing final drive ratios.

IVM-60 mph time was simulated by requesting a step input of 200 mph from vehicle rest. The control strategy in Autonomie provides all torque to the wheels to meet this demand. The time from one-foot rollout to 60 mph was then measured.

Competition requires a minimum IVM-60 mph time of 9.0 seconds. The team defined an OSU specific goal of 8.5 seconds to exceed customer VTS for consumer appeal. A 5% factor of safety was added to performance simulation results to ensure ability to meet VTS. Component combinations that did not meet this worst-case acceleration target were eliminated at this stage.

Additionally, all transmission ratio combinations were checked for overspeed limits at this phase, to eliminate infeasible final drive ratios. This was done according to Equation 7. Relevant assumptions and values are provided in Chapter 4. The wheel radius was given as 0.3718 m by competition sponsors and used to calculate the conversion to mph [7].

$$vehicle\ speed_{component\ limit} = hardware\ limit\,\frac{rev}{min} \times \frac{\frac{\pi}{30}\frac{rad}{s}}{\frac{rev}{min}} \times \frac{1}{gear\ ratio} \times \frac{0.83169\ \frac{miles}{hour}}{\frac{rad}{s}} \qquad [7]$$

3.5 Stage 4: Fuel Economy Simulations

The remaining component configurations from the performance simulations were then used in a final phase of energy consumption simulations. Autonomie and dynamic programming were used in conjunction to provide both realistic and ideal fuel economy estimates. The same stock hybrid architecture vehicle model from Stage 3 Autonomie was used. Overall fidelity was increased by replacing the stock component initialization files with specific data for the remaining engine, ESS, gearbox, and electric motor options. Vehicle models were created for each specific component combination, similar to Stage 3. At this stage, competition released the HDS battery pack as a secondary sponsored ESS option. All component efficiencies as well as models for torque converters, electrical and mechanical accessories, power converters, and tires were left stock. It was assumed industry-derived Autonomie data and models could be used as reasonable estimates.

To be able to appropriately compare between the different vehicle models, hybrid control strategy was optimized for each component configuration. This was done by identifying target variables to run through a particle swarm optimization (PSO). PSO is a stochastic population based global optimization method that does not require knowledge of the system equations or derivatives [18]. It works by initializing particles randomly within a given search space. These particles sweep randomly to find the minimum of an objective function, while communicating with each other. The general PSO algorithm is given by Equation 8.

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(pbest_i^k - x_i^k\right) + c_2 r_2 (gbest_i - x_i^k) \quad [8]$$

Where ωv_i^k is the cognitive component that keeps track of each particle's personal best position, $c_1 r_1 \left(pbest_i^k - x_i^k\right)$ is used to communicate with the swarm, directing the particle towards the global optimum position, and $c_2 r_2 (gbest_i - x_i^k)$ is the inertia component that affects the particles' exploration of new locations in the search space [18].

A swarm size of 96 particles was chosen with 120 iterations. The learning factors were set as follows: $c_1 = 0.75$ and $c_2 = 1.25$. These factors were determined after performing a sensitivity sweep to assess the impact of varying swarm size, number of iterations, and c_1 on convergence on the global minimum. C_2 was weighted higher than c_1 to ensure the swarm settles on the global minimum, rather than a local minimum [19]. The inertia component was governed by the function shown in Figure 8. This grants the particle swarm greater freedom to explore new locations initially and then gradually constrains particle movement more as they settle in on the global minimum.

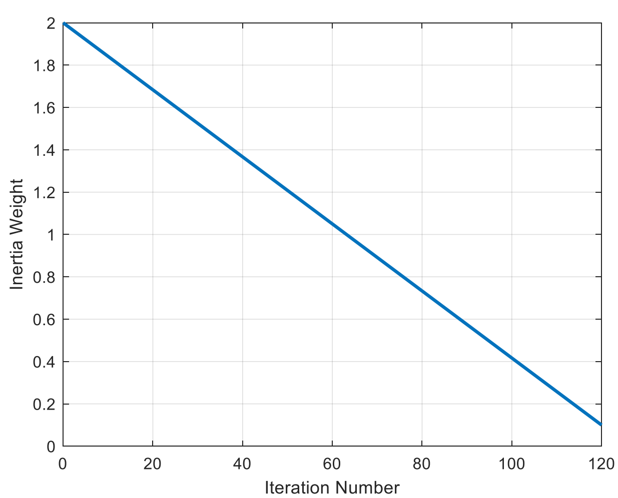


Figure 8: Inertia Weight Function

The specific variables used in the PSO are included in Table 12. These gains were chosen for their ability to affect both fuel economy and performance. Minimum and maximum limits for each gain were assumed based on the stock Autonomie values and used as optimization constraints.

Table 12: Autonomie Controller Variables for PSO

Variable Name	Variable Description	Initial	Min	Max
vpc.prop.init.eng_soc_ess_below_turn_on	SOC of the ESS below which the engine turns on	0.375	0.3	0.45
vpc.prop.init.eng_time_min_stay_off	Once off, minimum time for the engine to stay off	3 s	1 s	5 s
vpc.prop.init.eng_time_min_stay_on	Once on, Minimum time for the engine to stay on	3 s	1 s	5 s
vpc.prop.init.eng_pwr_whl_above_turn_on	Minimum power for the engine to turn on	51500 W	28000 W	75000 W
vpc.prop.init.eng_pwr_whl_below_turn_off	Maximum power for the engine to turn off	11500 W	1000 W	22000 W
vpc.prop.init.eng_time_min_pwr_dmd_above_thresh	Minimum time the wheel torque demand has to be above the threshold to turn the engine ON	1.75 s	0.5 s	3 s
vpc.prop.init.eng_time_min_pwr_dmd_below_thresh	Minimum time the wheel torque demand has to be below the threshold to turn the engine OFF	2 s	1 s	3 s
vpc.prop.init.perfo_time_min	Time used in the performance mode	0.05 s	0 s	0.1 s
vpc.prop.init.mot2_percent_max_low	percentage of mot_max_trq under which the engine can be off (REM)	0.55	0.3	0.8
vpc.prop.init.ess_percent_pwr_charged	percentage of the max battery power to be charged when SOC = vpc.prop.init.ess_soc_charge_intermediate_pwr	0.5	0.25	0.75
vpc.prop.init.ess_percent_pwr_discharged	percentage of the max battery power to be charged when SOC = vpc.prop.init.ess_soc_discharge_intermediate_pwr	0.5	0.25	0.75

The optimized controller values were then implemented for each specific component configuration. These vehicle models were simulated on the EMC City and Highway cycles and combined fuel economy results calculated. Component combinations that did not meet the stock Blazer fuel economy were eliminated.

The optimized Autonomie values provide a lower fuel economy estimate, which can be considered realistically achievable. Dynamic programming (DP) was used as a second phase, to calculate a theoretical upper limit of each configuration's fuel economy. This method assesses the optimal performance of a configuration without the need to formulate and calibrate an optimal controller. It consists of the DPM function developed by ETH Zurich, as well as the team-developed vehicle kinematics model. The DPM function performs backwards calculations on a drive cycle and vehicle model to determine the optimal solution at each time step to a given cost function [20]. It also runs forward simulations to ensure all control inputs are feasible. The final results are an optimized fuel economy as well as an overall simulation error based on accumulated interpolations made during the simulation. The vehicle model used with this function reflects the kinematics of the engine, transmission, and battery pack. It also models all infeasible behavior, such as over speeding components or exceeding a battery's charge or discharge limits. The results provided by dynamic programming reflect the theoretical fuel economy that could be achieved through proper integration, ideal control strategies, and implementation of CAV technology.

Combining both the Autonomie results and dynamic programming estimates bracketed the achievable fuel economy for each component configuration. A final architecture was then selected from the remaining design space, based on its capacity for fuel economy optimization.

3.6 Architecture Validation

After the determination of a final optimal architecture, the original VTS were then validated through accessory simulations. This included calculating vehicle top speed, as well as simulating 50-70 mph acceleration time and maximum gradeability. The latter two tests were done in Autonomie using the finalized architecture model.

Vehicle top speed was calculated based on gear ratios, according to Equation 9. Specific component limits were used to calculate the maximum achievable vehicle speed. Similar to Equation 7, the wheel radius was given as 0.3718 m and used to calculate the conversion to mph.

$$vehicle\ speed = component\ limit\ \frac{rev}{min} \times \frac{\frac{\pi}{30}\frac{rad}{s}}{\frac{rev}{min}} \times \frac{1}{gear\ ratios} \times \frac{0.83169\ \frac{miles}{hour}}{\frac{rad}{s}} \qquad [9]$$

The 50-70 mph test was performed by holding the vehicle at 50 mph for 180 seconds and then requesting a velocity step up to 70 mph. 180 seconds was used to ensure the vehicle had reached steady state at 50 mph prior to the additional velocity request. The time from accelerator pedal tip in to 70 mph was measured.

Maximum gradeability of the final architecture was determined by running a series of simulations at 60 mph for 20 minutes with a constant grade. A number of desired iterations was input and Autonomie increased the grade incrementally. The maximum grade was recorded once the vehicle could not follow the requested velocity trace within 0.1 mph.

CHAPTER 4: RESULTS

This chapter reports the results of each stage of the design space exploration described in Chapter 3. It concludes with evaluating the final architecture selection's ability to meet team VTS.

4.1 Stage 1: Hybrid Configuration Determination

GREET fuel economy and energy consumption estimates for conventional, HEV and PHEV configurations are shown in Figure 9. After analyzing competition events, it was determined that a PHEV would be unable to operate in charge sustaining (CS) mode. To reflect this, the PHEV CS mode was set to 0% vehicle miles travelled to prevent GREET from simulating charge sustaining operation.

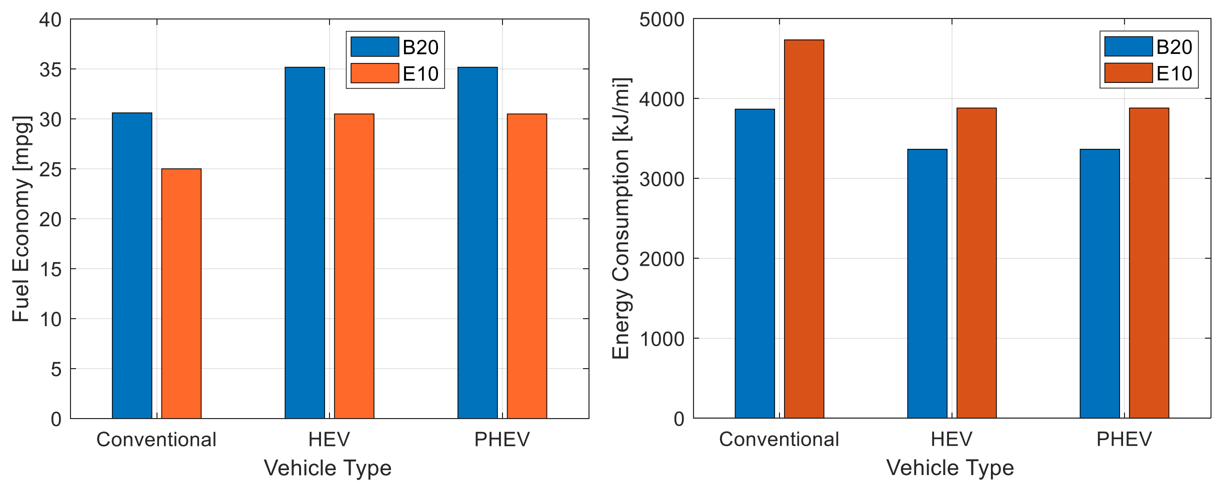


Figure 9: Hybrid Configuration Energy Consumption

The inability to take advantage of CS operation removes the benefit of a PHEV architecture. Thus, the HEV and PHEV show identical fuel economy and energy consumption. This simulation did not factor in the increased weight of a PHEV due to the need for a larger battery pack. This would result in a slight increase in both fuel economy and energy consumption while also posing a greater integration challenge. Thus, a PHEV architecture was removed from consideration.

In addition, the B20 resulted in higher fuel economy and lower energy consumption compared to E10. However, E10 was carried forward to continue evaluating a the various sponsored spark ignition engine options.

4.2 Stage 2: Electric Motor Configuration

The stock Autonomie models for different electric motor placements generated the fuel economy estimates shown in Figure 10.

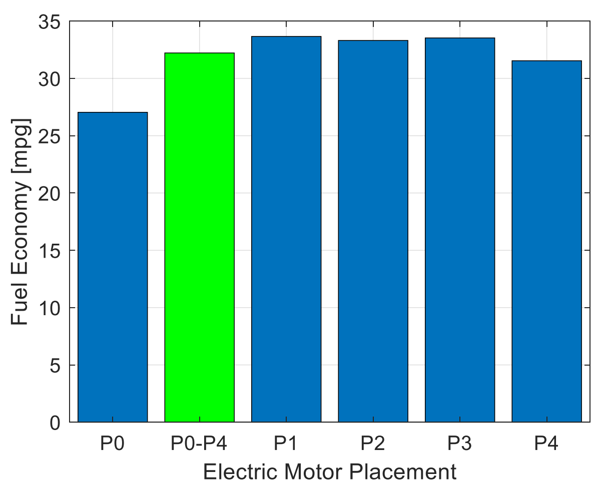


Figure 10: Impact of EM Placement on EMC Combined Fuel Economy

Although the P1, P2, and P3 options perform best, the gain in fuel economy is minimal compared to the P0-P4 and P4 motors. To help distinguish between motor configurations, the risk versus performance of these different motor configurations was further explored through analyzing EcoCAR 3 vehicles.

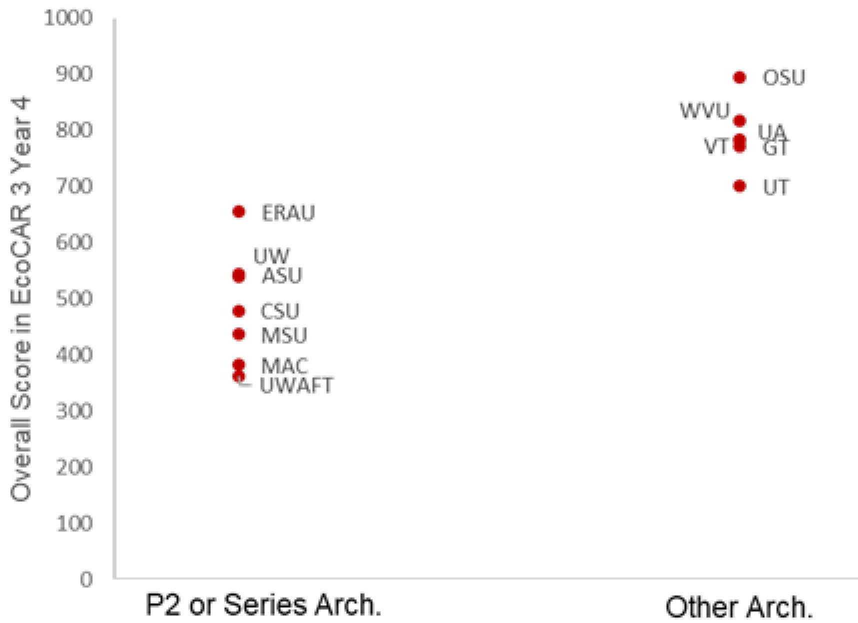


Figure 11: Architecture versus Performance

The risk associated selection of a P2 motor is reflected strongly in the previous competition cycle with many teams unable to compete as intended, resulting in a low overall competition score. From the literature review, both P1 and P2 motors pose greater integration risk as they necessitate splitting the engine and transmission. Finally, a P3 would require a custom gearbox to integrate into the existing architecture. From EcoCAR 3, custom gearboxes pose a significant challenge in regards to efficiency and noise, vibration, and hardness (NVH).

The minimal fuel economy benefit of the P1, P2, and P3 options was outweighed by their higher integration risk. The P0-P4 was chosen as a final option, achieving 32.22 mpg with unoptimized controls and generic component data.

The Monte Carlo simulation showed a slight statistical advantage for a high voltage system over a 48V variant. From the simulation data, the 48V P0-P4 won 48.55% of the competitions while the HV P0-P4 had a winning percentage of 51.45%. Because the high voltage system won more often over the 48 V variant, the second option was excluded from the design space.

4.3 Stage 3: Acceleration Simulations

The chosen performance metric of IVM-60 mph time was simulated in Autonomie for each specific component configuration. Although the results are dependent on four factors – engine, electric motor, front final drive ratio, and rear final drive ratio – the engine selection and electric motor sizing show the strongest impact on IVM-60 time, shown in Figure 12 and Figure 13 respectively. The team-defined 8.5 second performance cutoff was overlaid to demonstrate which configurations do not meet the maximum allowable team target. Figures show performance simulation results adjusted for 5% factor of safety.

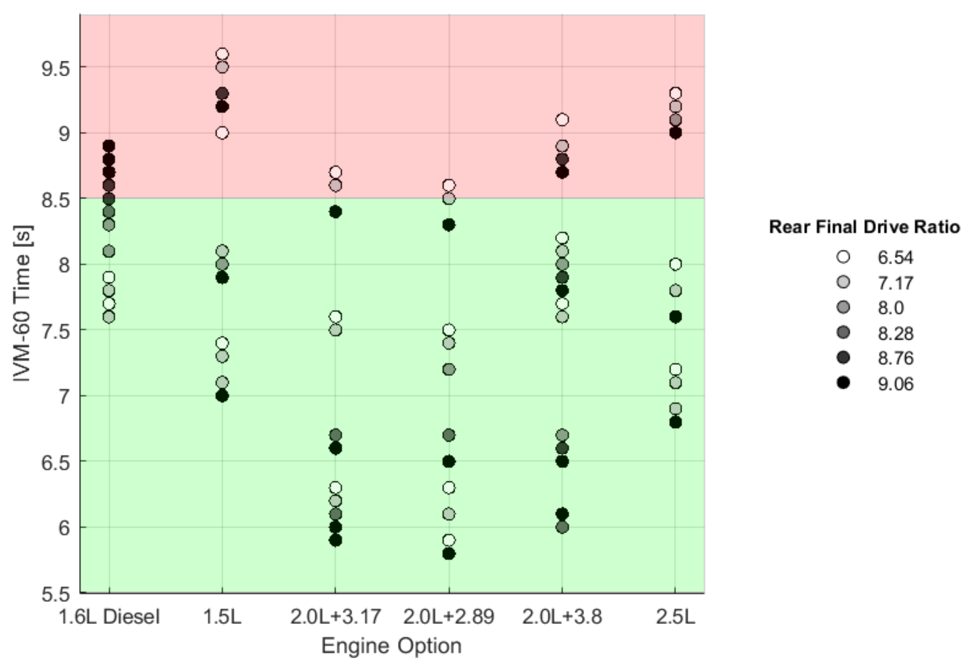


Figure 12: Engine Impact on IVM-60 Time

From Figure 12, the 2.0L turbocharged engine offers the best performance times when paired with the 3.17 and 2.89 front drive ratio options. The 1.6L diesel performs poorly overall, with varying the final drive ratio only offering a 1.3 second improvement. Due to the minimal optimization space available with this option, the diesel engine was removed from architecture consideration.

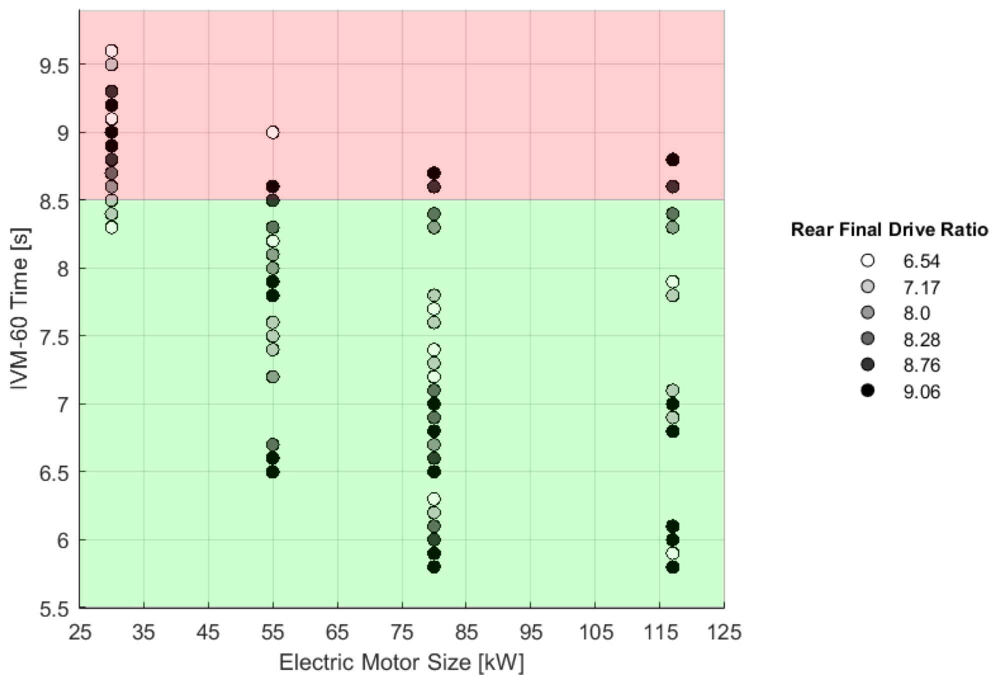


Figure 13: Electric Motor Impact on IVM-60 Time

Similar to the engine options, the size of the electric motor affected acceleration time, shown in Figure 13. The 30 kW motor was unable to meet the minimum acceleration target for the majority of the engine and rear final drive ratio combinations. Likewise, the 55 kW motor did not offer the same ability to achieve lower IVM-60 mph times as the 80 and 117 kW options. Both the 30 kW and 55 kW electric motors were removed from the design space at this stage.

The RPM for each rear final drive ratio was calculated and compared to the hardware limits for the engine and P0 and P4 motors. A sample calculation is provided in Equation 10 for the 9.06 final drive ratio. The competition dictates a top speed of 80.23 mph, according to the VTS in Table 1. 90 mph was used as the team top speed VTS to ensure components are not operating at their maximum capabilities. The wheel radius was assumed as 0.3718 m based on competition-provided information [7]. The P4 speed limit was provided by Borg Warner as 8,000 rpm.

$$speed_{P4} = 90\ \frac{miles}{hour} \times \frac{\frac{rad}{s}}{0.83169\ \frac{miles}{hour}} \times 9.06 \times \frac{\frac{rev}{min}}{\frac{\pi}{30}\frac{rad}{s}} = 9362.258\ rpm \qquad [10]$$

From Equation 10, the 8.76 and 9.06 final drive ratio options would cause the P4 to overspeed at maximum speed. Considering the elimination of the diesel engine, the 30 kW and 55 kW electric motors, and 8.76 and 9.06 final drive ratio options, the design space was reduced by 58.33%.

4.4 Stage 4: Fuel Economy Simulations

The remaining component configurations were used in fuel economy simulations to determine more accurate estimates. Autonomie results were first analyzed in a method similar to the performance metric in Stage 3. The stock Blazer fuel economy of 29.1 mpg was used as a minimum cutoff. Figure 14 and Figure 15 isolate the effect on fuel economy of the engine selection and rear drive ratio, respectively.

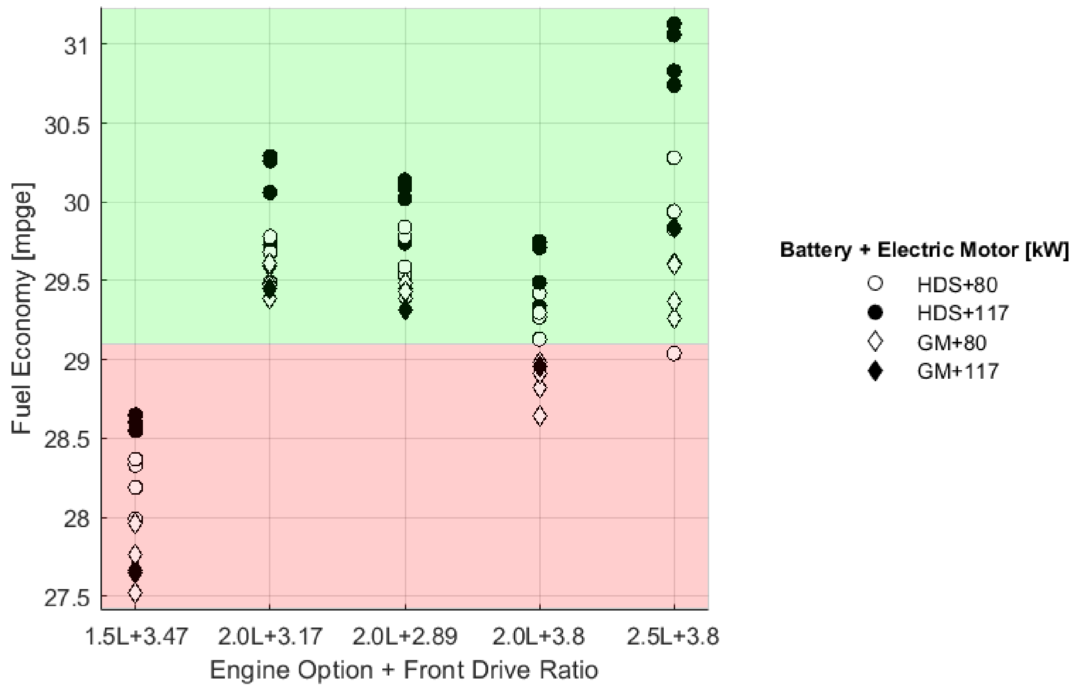


Figure 14: Engine Impact on Fuel Economy

All configurations of the 1.5L turbocharged engine failed to match the stock Blazer fuel economy, eliminating this engine option. In addition, some configurations of the 2.0L and 2.5L with a front drive ratio of 3.8 did not meet the minimum fuel economy and were removed from the design space as well.

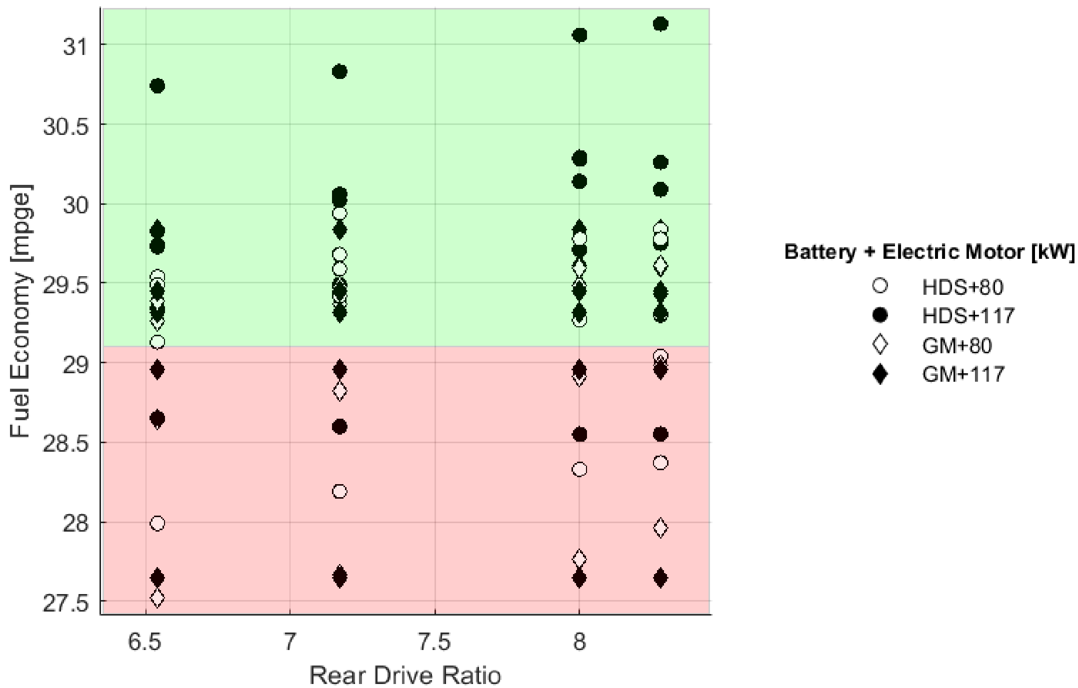


Figure 15: Rear Drive Ratio Impact on Fuel Economy

The rear drive ratio had a small impact on fuel economy, primarily showing that larger ratios offered slightly better fuel economy results. Overall, the HDS battery pack with the 117 kW motor showed the best fuel economy.

The same component configurations run in Autonomie were analyzed with DP to yield ideal fuel economies. Results are shown in Figure 16. Because all theoretical estimates were above the 29.1 mpge cutoff, color blocks were removed.

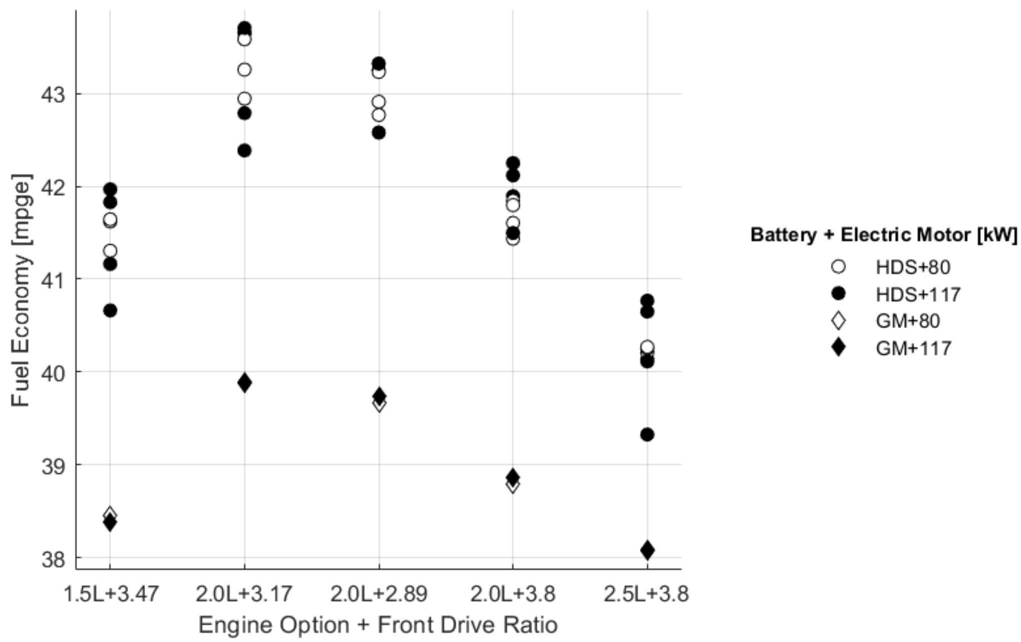


Figure 16: Optimal Fuel Economy for Engine Options

Dynamic programming shows the 2.0L turbocharged engine with the 3.17 front drive ratio offers the highest achievable fuel economy results. In addition, results showed the HDS pack, paired with both 80 and 117 kW P4 motors, offer higher fuel economy than the GM battery pack options. DP simulations show that the regenerative energy occasionally exceeded 62 kW, which is the peak power of the GM pack. This additional energy is unable to be captured by the smaller GM battery pack, contributing to the difference in fuel economy. The HDS pack and 117 kW P4 motor were selected for the final architecture due to their fuel economy benefit.

The results of both Autonomie and dynamic programming were combined to visualize the optimization space available for the remaining component configurations, shown in Figure 17. The lower bounds are given by Autonomie results and upper bounds by DP.

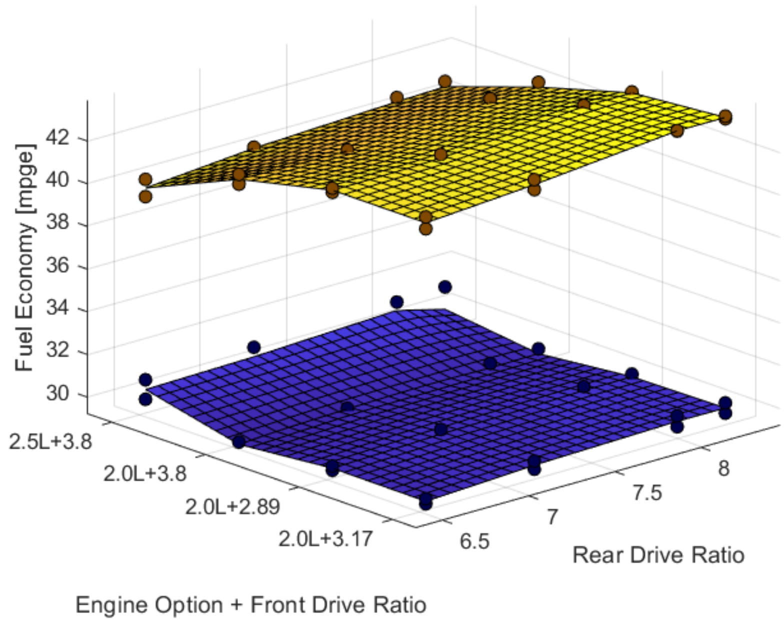


Figure 17: Simulated Fuel Economy Bounds

The engine and front drive ratio had the most significant impact on fuel economy and are presented in Figure 18.

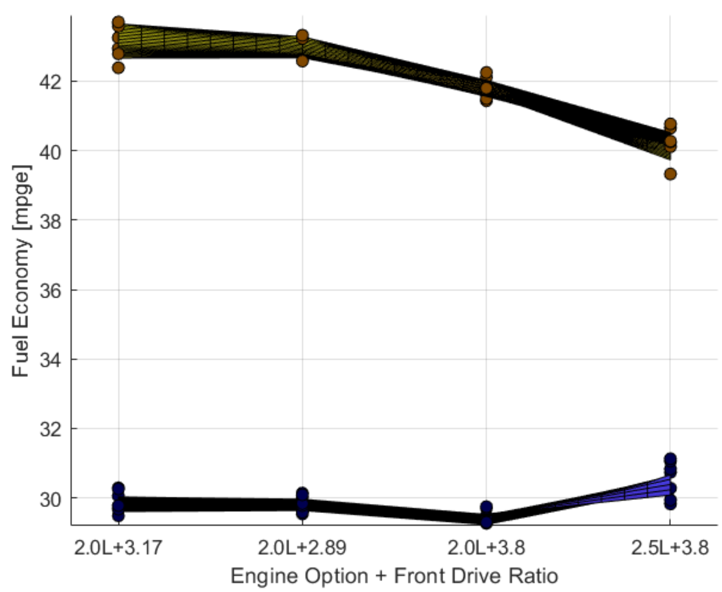


Figure 18: Impact of Engine Option on Fuel Economy

Overall, the lower limits show that the baseline performance of each engine option is comparable. This minimizes the risk of choosing a vehicle with significantly worse unoptimized performance. The upper limit reflects the theoretically achievable fuel economy through implementation of an ideal controller and use of V2X information. While the 2.5L NA engine had the highest baseline performance in Figure 18, it also had the lowest optimization ceiling. Comparatively, the 2.0L turbocharged engine with a front drive ratio of 3.17 showed the largest optimization space. This was chosen as the final engine option.

The conclusion of the design space exploration resulted in a final selected architecture of a P0-P4 with a 2.0L turbocharged engine, front drive ratio of 3.17, final drive ratio of 8.00, 117 kW electric motor and HDS battery pack.

4.5 Validation of VTS

The final architecture was tested for its ability to meet additional VTS. The vehicle top speed was calculated according to Equations 11-13, using the sponsor-provided values in Table 13.

Table 13: Overspeed Limit Assumptions

Front Drive Ratio	Transmission Ratio	BAS Ratio	Rear Drive Ratio	Wheel Radius [m]	REM Limit [rpm]	BAS Limit [rpm]	Engine Limit [rpm]
3.17	0.6170	2.5	8.0	0.3718	8000	21000	7000

$$vehicle\ speed_{P4\ limit} = 8000\ \frac{rev}{min} \times \frac{\frac{\pi}{30}\frac{rad}{s}}{\frac{rev}{min}} \times \frac{1}{8.0} \times \frac{0.83169\ \frac{miles}{hour}}{\frac{rad}{s}} = 87.095\ mph \qquad [11]$$

$$vehicle\ speed_{P0\ limit} = 21000\ \frac{rev}{min} \times \frac{\frac{\pi}{30}\frac{rad}{s}}{\frac{rev}{min}} \times \frac{1}{3.17} \times \frac{1}{0.6170} \times \frac{1}{2.5} \times \frac{0.83169\ \frac{miles}{hour}}{\frac{rad}{s}} \qquad [12]$$

$$= 374.046\ mph$$

$$vehicle\ speed_{engine\ limit} = 7000\ \frac{rev}{min} \times \frac{\frac{\pi}{30}\frac{rad}{s}}{\frac{rev}{min}} \times \frac{1}{3.17} \times \frac{1}{0.6170} \times \frac{0.83169\ \frac{miles}{hour}}{\frac{rad}{s}} = 311.706\ mph \qquad [13]$$

From the calculations, the architecture is limited by the hardware limit of the P4 motor to a maximum of 87.095 mph. This provides an 8.56% factor of safety for the competition-required top speed of 80.23 mph.

The 50-70 mph acceleration time and maximum gradeability were tested in Autonomie, using the final P0-P4 model from Stage 4. All results are recorded in Table 14, alongside of the original requirements [6].

Table 14: OSU Vehicle Technical Specification Validation

Specification	Competition Target	Minimum Requirement	Simulation Results
Acceleration, IVM-60 mph [s]	6.0	9.0	6.3
Acceleration, 50-70 mph (Passing) [s]	6.5	TBD	3.3
Fuel Economy [mpg]	33.5	Stock	32.53
Emissions	Stock	Stock	Stock
Gradeability [% grade @ 60 mph for 20 minutes]	3.5	N/A	16.0
Vehicle Top Speed [mph]	80.23	80.23	87.095

From the simulation results, the proposed architecture meets all requirements.

In conclusion, the results of the design space exploration resulted in a final proposed architecture of a P0-P4 with a 2.0L turbocharged engine, front drive of 3.17, final drive of 8.00, 117 kW electric motor and HDS battery pack. This architecture meets all team VTS for baseline performance. In addition, this component configuration offers the greatest ability to optimize for fuel economy with an ideal control strategy.

CHAPTER 5: CONCLUSION

5.1 Summary

The architecture selection process presented above reflects a hybrid vehicle design space exploration aiming to optimize fuel economy while maintaining performance characteristics of a 2019 GM Blazer for the EcoCAR Mobility Challenge. The constraints of competition outlined the initial design space. This was first refined through high-level, simple simulations to eliminate fuel options, hybrid configurations, and electric motor placements. The later stages focus on evaluating the ability of different component configurations to meet specific performance and fuel economy targets. The final proposed architecture is a P0-P4 with a 2.0L turbocharged engine, front drive ratio of 3.17, final drive ratio of 8.00, a 117 kW electric motor, and the HDS battery pack. It was validated for its baseline ability to meet all team VTS.

The proposed architecture and selection process will be presented by the Ohio State University EcoCAR team at the conclusion of Year 1. This sets the stage for the remaining years of competition, which will focus on the design and implementation of the proposed architecture.

5.2 Future Work

While baseline performance of the P0-P4 is expected to meet team VTS, the 2.0L turbocharged engine was chosen specifically for its ability to optimize for fuel economy. This provides an avenue of continued research in controller development and CAV technology implementation.

The vehicle models used in this design space exploration either utilized Autonomie's prebuilt controllers, with some limited optimization, or reflected an ideal controller with dynamic programming's backward calculating math function. Upon selection of the final architecture, a vehicle plant model and controller must be created in Simulink. The plant model will be a mapped-based model, relying on the same provided supplier data as Autonomie and DP.

Component testing can be performed to acquire more accurate data for given use cases, test conditions, and specific models. The overall control structure will be developed in conjunction with the plant model. As more accurate component data is implemented, control strategies will be adjusted. After initial development, the team will move first to Model-in-the-Loop (MIL) and then Vehicle-in-the-Loop (VIL) testing to evaluate the controller's functionality. Model portability throughout the XIL process will be a major influence on the controller and plant design.

A key point of development for the controller will be the energy management strategy. This will determine the vehicle's ability to minimize fuel consumption. On a very basic level, the controller must determine the vehicle's mode of operation, hybrid torque split, and gear state. DP rules extraction will determine the vehicle's mode of operation, series or parallel, given the torque request. In conjunction with the rule-based mode of operation determination, the hybrid torque split and gear state will be influenced by Equivalent Consumption Minimization Strategy (ECMS). This is a real-time energy management for HEVs that, given a well-defined cost function that equates electrical and liquid fuel energies, solves for the instantaneous minimum [21]. Given that ECMS solves for the global minimum at each time step, its control outputs may cause rapid oscillations that would negatively affect drive quality. To mitigate this, the output of ECMS will be used to influence the controller's torque split and gear state decisions but not have full control over the final request. Integration of DP rules extraction and ECMS will form the baseline vehicle controller.

To move beyond baseline performance, the ability to receive and implement CAV technology must be implemented in the controller. While ECMS optimizes based on instantaneous parameters, DP solves for the fuel cost function's global minimum with its backward algorithm.

However, this requires a priori knowledge of the drive trace and conditions, making DP not suitable for real-time implementation on conventionally-driven vehicles [21]. With the focus on CAVs technology in Years 3 and 4 of the EMC, real-time DP may be able to take advantage of V2X information transmitted by the CAV system.

While the scope of the V2X data is not yet confirmed by competition, this will most likely include Vehicle to Vehicle (V2V) as well as Vehicle to Infrastructure (V2I) signals. These signals will provide the car with ‘future’ information, such as an upcoming light change. Knowledge of the immediate future along with route planning information may provide DP enough information to feasibly implement real-time DP. This would allow the controller to globally optimize for fuel economy, approaching the theoretical fuel economy estimates initially provided by DP in Stage 4 of the architecture selection process.

APPENDIX A

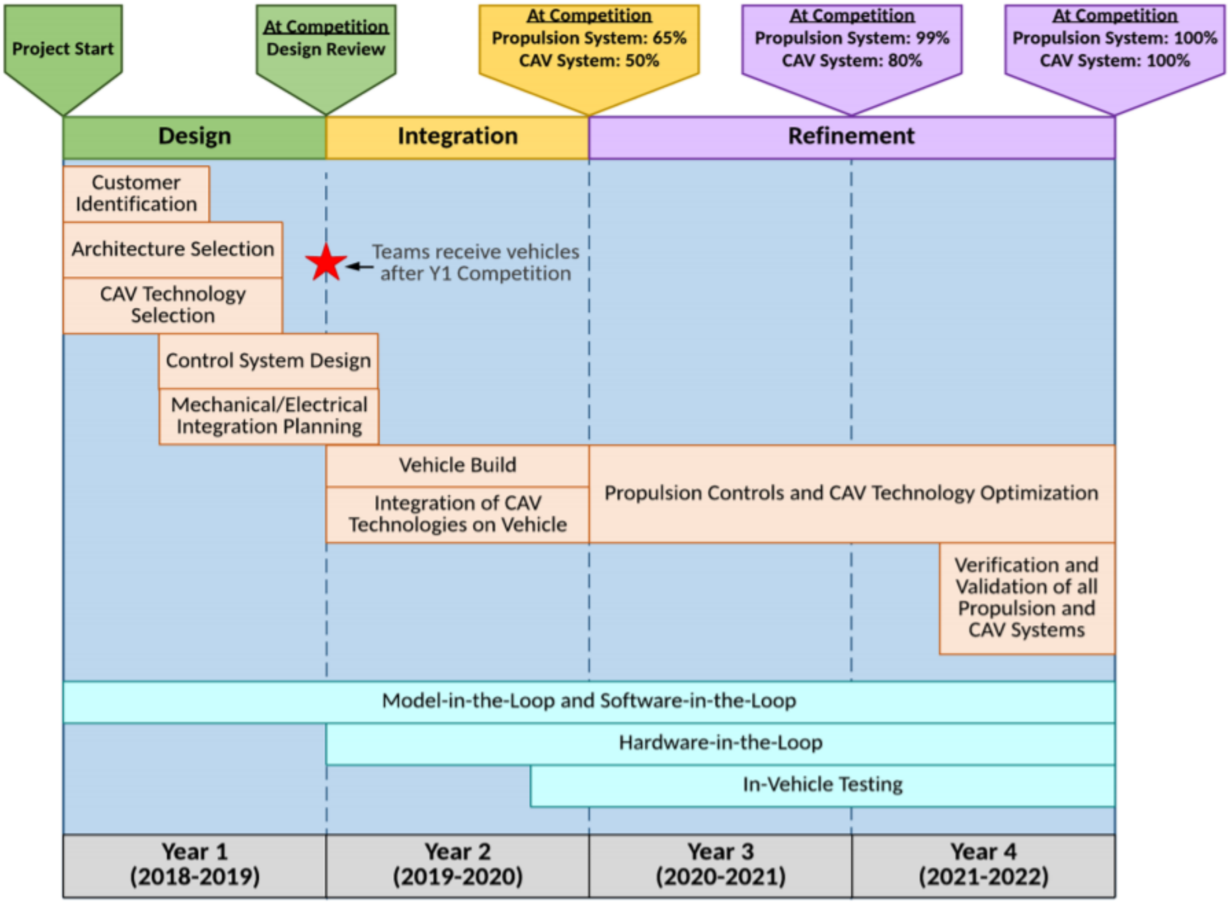


Figure 19: EcoCAR Mobility Challenge Vehicle Development Process

Cost of Ownership

```
close all
clear
clc
% Monte Carlo Simulation for randomly selected HV P0, 48V P0, HV P0-P4, 48V

%% Cost Model from EMC Y1 FW MaaS Customer Paradigm and Cost System Model
Proposal
%Assume Lifetime Ownership is 18 months
%%%%% Purchase Price %%%%%
%motor kW estimates
P048V_kW_motor_Team = [12 15];
P0HV_kW_motor_Team = 30;
P0P448V_kW_motor_Team = [36 39];
P0P4HV_kW_motor_Team = [60 200];
%battery kW estimates
P048V_kW_battery = 14;
P0HV_kW_battery = 62;
P0P448V_kW_battery = 42;
P0P4HV_kW_battery = [62 110];
%Motor Cost
```

```
P048V_Motor_Cost_Team = 6.*P048V_kW_motor_Team; % $
P0HV_Motor_Cost_Team = 6.*P0HV_kW_motor_Team; % $
P0P448V_Motor_Cost_Team = 6.*P0P448V_kW_motor_Team; % $
P0P4HV_Motor_Cost_Team = 6.*P0P4HV_kW_motor_Team; % $
%Battery Cost
P048V_Battery_Cost_Team = 20.*P048V_kW_battery; % $
P0HV_Battery_Cost_Team = 20.*P0HV_kW_battery; % $
P0P448V_Battery_Cost_Team = 20.*P0P448V_kW_battery; % $
P0P4HV_Battery_Cost_Team = 20.*P0P4HV_kW_battery; % $
%Number of Cylinders
NoCyl_team = 4;
NoCyl_stock=6;
%Engine Power - assuming kW not HP
EngPwr_team =205.067; %kW
%GM 1.5L=126.769
%Ford Diesel=120.803
%GM Diesel=102
%GM2.0L=205.067
%GM 2.5 L=149.14
EngPwr_stock=227.438;
%EngPwr_stock_2=143.92;
%Direct injection
DI_team = 1;
DI_stock=1;
%Turbo - assuming this means how much additional power the turbo charger
provides
Boost_team = 1;
Boost_stock=0;
%Spark Ignited
Engine_Cost_SI_team =
827+(109*NoCyl_team)+(6.2*EngPwr_team)+(283*DI_team)+(1730*Boost_team);
Engine_Cost_stock =
827+(109*NoCyl_stock)+(6.2*EngPwr_stock)+(283*DI_stock)+(1730*Boost_stock);
%Compresssion Ignited
%Engine_Cost_SI_team = 1294+(518*NoCyl_team)+(8.05*EngPwr_team);

%PropSys Cost
P048V_Team_PropSys_Cost =
P048V_Motor_Cost_Team+P048V_Battery_Cost_Team+Engine_Cost_SI_team;
P0HV_Team_PropSys_Cost =
P0HV_Motor_Cost_Team+P0HV_Battery_Cost_Team+Engine_Cost_SI_team;
P0P448V_Team_PropSys_Cost =
P0P448V_Motor_Cost_Team+P0P448V_Battery_Cost_Team+Engine_Cost_SI_team;
P0P4HV_Team_PropSys_Cost =
P0P4HV_Motor_Cost_Team+P0P4HV_Battery_Cost_Team+Engine_Cost_SI_team;
Stock_PropSys_Cost = Engine_Cost_stock;   %Stock option
% Team_PropSys_Cost =
Motor_Cost_team+Battery_Cost_team+Engine_Cost_CI_team;    %CI Team option
% Stock_PropSys_Cost =
Motor_Cost_stock+Battery_Cost_stock+Engine_Cost_CI_stock;   %CI stock option

%Purchase Price
P048V_Purchase_Price = P048V_Team_PropSys_Cost- Stock_PropSys_Cost;
P0HV_Purchase_Price = P0HV_Team_PropSys_Cost- Stock_PropSys_Cost;
P0P448V_Purchase_Price = P0P448V_Team_PropSys_Cost- Stock_PropSys_Cost;
P0P4HV_Purchase_Price = P0P4HV_Team_PropSys_Cost- Stock_PropSys_Cost;
%%%%% Total Fuel Cost %%%%%
```

```
%Fuel Price
%Fuel_Price = 3.43; % Diesel $/gal
Fuel_Price = 3.19; %Regular Gas $/gal

%Lifetime_Mileage
Lifetime_Mileage = 30000; %mi

%Fuel Economy
Fuel_Economy = 33.5; %mpg - 15% improvement over stock

%Total Fuel Cost
Total_Fuel_Cost = (Fuel_Price*Lifetime_Mileage)/Fuel_Economy;

%%%%% Resale Price %%%%%

%Depreciation
Depreciation = 0.25; %given

%Resale Price
P048V_Resale_Price = P048V_Purchase_Price * (1 - Depreciation);
P0HV_Resale_Price = P0HV_Purchase_Price * (1 - Depreciation);
P0P448V_Resale_Price = P0P448V_Purchase_Price * (1 - Depreciation);
P0P4HV_Resale_Price = P0P4HV_Purchase_Price * (1 - Depreciation);

%%%%% Total Ownership Cost %%%%%
P048V_Total_Ownership_Cost = P048V_Purchase_Price+Total_Fuel_Cost -
P048V_Resale_Price;
P0HV_Total_Ownership_Cost = P0HV_Purchase_Price+Total_Fuel_Cost -
P0HV_Resale_Price;
P0P448V_Total_Ownership_Cost = P0P448V_Purchase_Price+Total_Fuel_Cost -
P0P448V_Resale_Price;
P0P4HV_Total_Ownership_Cost = P0P4HV_Purchase_Price+Total_Fuel_Cost -
P0P4HV_Resale_Price;
```

Monte Carlo Simulation

```
%% Analysis Parameters
fe_threshold = 29.1; %minimum required fe to receive full completion pts
IVM60_thresh = 9.0; %maximum 0-60 required to receive full completion pts

% Point range for events for Y3
%note: this is points avaialable after the points for finishing + meeting
%threshold is applied
costPts_range = [21,28];
effPts_range = [87.75,94.25];
maxPerfPts = 45;

% Vehicle Parameters (with ranges and/or uncertainty)
%Fuel_economy - base fuel economy, 15% improvement over stock
stock_FE = 29.1; %mpg, assumed
P048V_FE_est = 1.01*stock_FE;
P0HV_FE_est = 1.015*stock_FE;
P0P448V_FE_est = 1.025*stock_FE;
P0P4HV_FE_est = 1.03*stock_FE;
FE_std = 3.5; %fuel economy standard deviation
```

```
FE_v = 3; %variance for Rayleigh distribution

%IVM-60 mph performance - assume same performance
IVM_60_est = 8.5;
IVM60_std = 0.5;

%% Competition Event
n = 50000;
for i = 1:n
%n = 50000; %number of iterations to run
m = 12; %number of vehicles per competition
% random distribution of vehicles that sums to 12
rsum = 0;
while rsum ~= m
    r = rand(1,4);
    r = round((r/sum(r))*m);
    rsum = sum(r);
end

P048V_m = r(1);
P0HV_m = r(2);
P0P448V_m = r(3);
P0P4HV_m = r(4);

% Generate Sample Pts based on Uncertainties
%competition points
costPts(i,:) = (costPts_range(2)-
costPts_range(1))*rand(1,1)+costPts_range(1);
effPts(i,:) = (effPts_range(2)-effPts_range(1))*rand(1,1)+effPts_range(1);

%fuel economy
P048V_FE = FE_std*randn(1,P048V_m)+P048V_FE_est;
P0HV_FE = FE_std*randn(1,P0HV_m)+P0HV_FE_est;
P0P448V_FE = FE_std*randn(1,P0P448V_m)+P0P448V_FE_est;
P0P4HV_FE = FE_std*randn(1,P0P4HV_m)+P0P4HV_FE_est;
FE_list(i,:) = [P048V_FE,P0HV_FE,P0P448V_FE,P0P4HV_FE];

%ownership cost
P048V_cost = (P048V_Total_Ownership_Cost(2)-
P048V_Total_Ownership_Cost(1))*randn(1,P048V_m)+P048V_Total_Ownership_Cost(1)
;
P0HV_cost = randn(1,P0HV_m)+P0HV_Total_Ownership_Cost;
P0P448V_cost = (P0P448V_Total_Ownership_Cost(2)-
P0P448V_Total_Ownership_Cost(1))*randn(1,P0P448V_m)+P0P448V_Total_Ownership_C
ost(1);
P0P4HV_cost = (P0P4HV_Total_Ownership_Cost(2)-
P0P4HV_Total_Ownership_Cost(1))*randn(1,P0P4HV_m)+P0P4HV_Total_Ownership_Cost
(1);
cost_list(i,:) = [P048V_cost,P0HV_cost,P0P448V_cost,P0P4HV_cost];

%IVM-60 mph performance
P048V_IVM60 = FE_std*randn(1,P048V_m)+IVM_60_est;
P0HV_IVM60 = FE_std*randn(1,P0HV_m)+IVM_60_est;
P0P448V_IVM60 = FE_std*randn(1,P0P448V_m)+IVM_60_est;
P0P4HV_IVM60 = FE_std*randn(1,P0P4HV_m)+IVM_60_est;
IVM60_list(i,:) = [P048V_IVM60,P0HV_IVM60,P0P448V_IVM60,P0P4HV_IVM60];
end
```

```
%% Run analysis for all pts
totalPts = zeros(n,m);

for i=1:n
    for j=1:m
         fe_pts =
fe_event_pts(costPts(i),effPts(i),FE_list(i,j),FE_list(i,:),cost_list(i,j),co
st_list(i,:),fe_threshold);
         perf_pts =
performance_event_pts(maxPerfPts,IVM60_list(i,j),IVM60_list(i,:),IVM60_thresh
);
         totalPts(i,j) = fe_pts+perf_pts;
    end
end

P048V_totalPts = reshape(totalPts(:,1:P048V_m),1,[]);
P0HV_totalPts = reshape(totalPts(:,1:P0HV_m),1,[]);
P0P448V_totalPts = reshape(totalPts(:,1:P0P448V_m),1,[]);
P0P4HV_totalPts = reshape(totalPts(:,1:P0P4HV_m),1,[]);

[pts,ind] = max(totalPts,[],2);

P048V_Win = (ind<=P048V_m);
P0HV_Win = (ind<=P0HV_m);
P0P448V_Win = (ind<=P0P448V_m);
P0P4HV_win = (ind<=P0P4HV_m);
totalmean =
mean(P048V_Win)+mean(P0HV_Win)+mean(P0P448V_Win)+mean(P0P4HV_win);

P048V_WinPercent = (mean(P048V_Win)/totalmean)*100;
P0HV_WinPercent = (mean(P0HV_Win)/totalmean)*100;
P0P448V_WinPercent = (mean(P0P448V_Win)/totalmean)*100;
P0P4HV_WinPercent = (mean(P0P4HV_win)/totalmean)*100;

clr = jet(4);

figure
subplot(4,1,1);
hold on
h1 = histogram(P048V_totalPts,'FaceColor',clr(1,:));
ylim([0 0.03]);
yticks([0 0.005 0.01 0.015 0.02 0.025 0.03]);
legend('P0_4_8_V');
grid on
xlabel('Total Points');
ylabel('Frequency');
hold off
subplot(4,1,2);
hold on
h2 = histogram(P0HV_totalPts,'FaceColor',clr(2,:));
ylim([0 0.03]);
yticks([0 0.005 0.01 0.015 0.02 0.025 0.03]);
legend('P0_H_V');
grid on
xlabel('Total Points');
ylabel('Frequency');
```

```
hold off
subplot(4,1,3);
hold on
h3 = histogram(P0P448V_totalPts,'FaceColor',clr(3,:));
ylim([0 0.03]);
yticks([0 0.005 0.01 0.015 0.02 0.025 0.03]);
legend('P0-P4_4_8_V');
grid on
xlabel('Total Points');
ylabel('Frequency');
hold off
subplot(4,1,4);
hold on
h4 = histogram(P0P4HV_totalPts,'FaceColor',clr(4,:));
ylim([0 0.03]);
yticks([0 0.005 0.01 0.015 0.02 0.025 0.03]);
legend('P0-P4_H_V');
grid on
xlabel('Total Points');
ylabel('Frequency');
h1.Normalization = 'pdf';
h2.Normalization = 'pdf';
h3.Normalization = 'pdf';
h4.Normalization = 'pdf';
hold off
```

BIBLIOGRPAPHY

[1] "Energy Flow Charts," Lawrence Livermore National Laboratory, 2017. [Online]. Available: https://flowcharts.llnl.gov/commodities/energy. [Accessed 4 October 2018].

[2] G. Rizzoni, *Hybrid-Electric Powertrains: Motivation, Technology, and Future Prospects,* Columbus, OH, 2018.

[3] H. Ritchie and M. Roser, "Fossil Fuels," Our World in Data, 2018. [Online]. Available: https://ourworldindata.org/fossil-fuels. [Accessed 28 November 2018].

[4] A. Selamet, *Internal Combustion Engines, Lecture 7,* Columbus, 2018.

[5] J. Gover, "A Tutorial on Hybrid Electric Vehicles: EV, HEV, PHEV, and FCEV," SAE, Michigan, 2020.

[6] "EcoCAR Non-Year Specific Rules," Argonne National Laboratory, 2019.

[7] *EcoCAR Mobility Challenge Fall Workshop,* Detroit: Argonne National Laboratory, 2018.

[8] J. R. Josephson, B. Chandrasekaran, M. Carroll, N. Iyer, B. Wasacz, G. Rizzoni, Q. Li and D. A. Erb, "An Architecture for Exploring Large Design Spaces," The Ohio State Universiy, Columbus, 1998.

[9] J. Josephson, B. Chandrasekaran, M. Carroll and T. Slavin, *Software Technology for Exploring Large Design Spaces,* Columbus: The Ohio State University, 2002.

[10] A. Emadi, K. Rajashekara, S. S. Williamson and S. M. Lukic, "Topological overview of hybrid electric and fuel cell vehicular power system architectures and configurations," *IEEE Transactions on Vehicular Technology,* vol. 54, no. 3, pp. 763-770, 2005.

[11] "Mild Hybrid Electric Vehicle (MHEV) - architectures," X-Engineer, 2019. [Online]. Available: https://x-engineer.org/automotive-engineering/vehicle/hybrid/mild-hybrid-electric-vehicle-mhev-architectures/. [Accessed 24 March 2019].

[12] "EcoCAR 3 Year 4 Results," Argonne National Laboratory , 2018.

[13] J. Karl-DeFrain, K. Kuwabara and C. Teece, "EcoCAR 3 Architecture Study," The Ohio State University, Columbus, 2018.

[14] US Department of Energy, "Energy Systems: GREET Model," Argonne National Laboratory, 2018. [Online]. Available: https://greet.es.anl.gov/. [Accessed 13 March 2019].

[15] US Department of Energy, "Autonomie," Argonne National Laboratory, [Online]. Available: https://www.autonomie.net/expertise/Autonomie.html. [Accessed 13 March 2019].

[16] C. H. Xia, "ISE 6300: Monte Carlo Simulation," Ohio State University, Columbus, 2019.

[17] B. McKay, *48V Architectures for Enabling High Efficiency,* Washington: Continential AG, 2016.

[18] M. Canova, *MECHENG 4999: Model Parametrization and Introduction to Optimization,* Columbus: The Ohio State University, 2018.

[19] J. Xin, G. Chen and Y. Hai, "A Particle Swarm Optimizer with Multi-stage Linearly-Decreasing Intertia Weight," *2009 International Joint Conference on Computational Sciences and Optimization,* pp. 505-508, 2009.

[20] O. Sundstrom and L. Guzzella, "A generic dynamic progamming Matlab function," *Control Applications, (CCA) & Intelligent Control, (ISIC),* pp. 1625, 1630, 2009.

[21] C. Musardo, G. Rizzoni, Y. Guezennec and B. Staccia, "A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management," *European Journal of Control,* vol. 11, no. 4-5, pp. 509-524, 2005.